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Wuhan International Conference on e-Business

Summer 5-26-2017

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Abstract: Consumer preference is a hot topic in the domain of marking management and e-commerce. Many previous studies have been conducted in this field. Whereas, there are rarely studies building on the particular commodity such as laptop. Therefore, this study explores comprehensive features that affect consumer preference for laptops by mining the online reviews. Firstly, we collect 6531 online reviews for Acer laptop from Amazon.cn and code these reviews with Nvivo10. Secondly, we develop a feature-based consumer preference model named MCPL based on the review text analysis. Considering the data imbalance of the collected 6531 product reviews, we adopt a random cluster sampling method to extract 50 groups with 100 samples per group. Then the correspondent regression analyses are conducted for the 50 groups of reviews. Finally, the meta-analysis is creatively conducted to integrate the multiple liner regression results of different groups. According to the result of meta-analysis, we demonstrate dominant features on behalf of the consumer preference of laptop and draw practical implications for enterprise competition strategies to facilitate product design or improvement.

Keywords: Consumer preference, Laptop, Online reviews, Meta-analysis

1. INTRODUCTION

The explosive growth of the internet and globalization of economy have led to fierce competition of global laptop computer market. A survey of IDC and Intel showed that 97% families in America took PC as their main devices in 2014. Among all kinds of personal computers, the laptop is used popularly because of its portability and convenience [1]. However, enormous different brands of laptop emerged in the market in the past years, which intensified the competition between notebook computers brands. In the first quarter of 2016, the recession reached 19%, felled by 7.3% comparing with 2015. In consequence, a better understanding of product feature preferences is beneficial for laptop designers, manufactures and marketers to formulate design and sale strategy, identify product defects and launch competitive products.

Consumer preference has always been a hot topic in the domain of marking management and e-commerce. Many previous studies have been conducted in the consumer preference. But there are rarely studies building on the particular commodity such as laptop, and most of them only concentrate on some specific characteristics of the laptop. The Attitude Theory has some implications for consumer satisfaction researches because it reveals the necessity of considering the consumer's evaluative (satisfaction/ dissatisfaction) response to obtained attributes. In fact, consumers tend to assess products in some particular features according to their own preferences, instead of the products' overall properties. Therefore, a feature-based perspective of opinion mining may perform better in understanding consumers' preferences. Besides, it can also be more helpful in understanding the product clearly and comparing it with competitors' products. Therefore, this study aims to fulfill the insufficient field of exploring comprehensive features that affect consumer preference for laptops.

Most previous studies used questionnaire to collect empirical data to research consumer behavior. Different from them, we use the online reviews in electronic commerce to analyze the consumer preference of laptops. The text comments of online reviews are coded with product and service features in order to transform them into quantitative datasets. The consumer preference model is developed base on the coding results. Finally, the regression and meta-analysis are conducted to verify the consumer preference model.

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The remainder of the paper is organized as follows. Section 2 reviews the literature relevant to this study. The conceptual model is proposed in Section 3. Section 4 reveals the methodology of our research. In Section 5, we describe our data processing and analysis procedure, and detail our proposed model MCPL for estimating aggregate consumer preferences from online product reviews. The results of our study are displayed in section 6. We conclude in Section 7 by highlighting our theoretical and practical contributions as well as some further research directions.

2. LITERATURE REVIEW

Consumer preference is defined as the likelihood to choose one commodity over another in the marketing term [2]. In the field of psychology, it is viewed as an individual's attitude towards a set of objects that stimulate one’s behavior in the decision -making process. Consumer preference is one of the most important factors related to whether a purchase will be made or not, and which specific objects will be chosen. Furthermore, consumer preference is graded into various types such as scenario preference, object preference, model preference, and so on [3].

The exploration of consumer preference has a long history. A large amount of the previous researches concentrated on the influential attributes of consumer preference, consumer satisfaction and consumer behavior. Apparently, there are inherent connections among the above notions. That is, consumer behavior is largely led by consumer preference [3] and consumer satisfaction [4], while consumer preference can be comprehended through consumer satisfaction and in return has an influence on it [2]. A good understanding of factors influencing consumer preference will be helpful for us to realize the strengths and weaknesses of the product and achieve a product improvement efficiently. The influential factors we found in previous researches are summarized in Figure 1.

Even though plenty of scholars have been generalizing the contributory factor of consumer preference, only a small fraction of them aim at a particular product, and most of them focus on several specific attributes [18]-[20]. Thus, we concentrate on the complete features mining of a product from the consumer reviews.

With respect to the data collection, traditional methods can be roughly divided into two groups: survey data based approaches and behavioral data based approaches [21]. The former one includes questionnaire [22]-[24], interview [18], literature review [25], [26], or the integration use of both [18]. In the era of big data, applying text-mining of external data sources to investigate consumer preference become a novel trend [27]-[31]. Product attributes extracted from online reviews are more reliable. Besides, comparing to the traditional ones, the review-based means are proved to be more favorable, because it is not only economical but also time-saving. That’s why we choose it in our research. Additionally, Amarouche [30] concludes that there are 3 layer of opinion mining from review including whole opinion level, sentence level and feature level. Our research takes the last one.

In terms of data analysis, there are also plenty of methodologies, such as factor analysis, PCA (principal component analysis) [20], Bayesian estimation methods, Markov chain Monte Carlo simulation inference [21], [32], fuzzy analytical approach [20], and so on. Rangaswamy [4] makes a conclusion of relative approaches, which include research method and design, realism philosophies, deductive approaches, quantitative research method, survey strategies, mono method, cross-sectional analysis, descriptive research design, questionnaires research instrument. Except for the above-mentioned methods, the conjoint analysis turns out to be more pervasive [1], [3], [21], [34], [35]. Moreover, as Varela [36] proved, preference ranking coupled with open comments turns out to be more useful compared with a more classic approach using a 9-point hedonic scale coupled with intensity questions. Hence, we aim at ranking the influence of separate feature on account of the correlation coefficients.

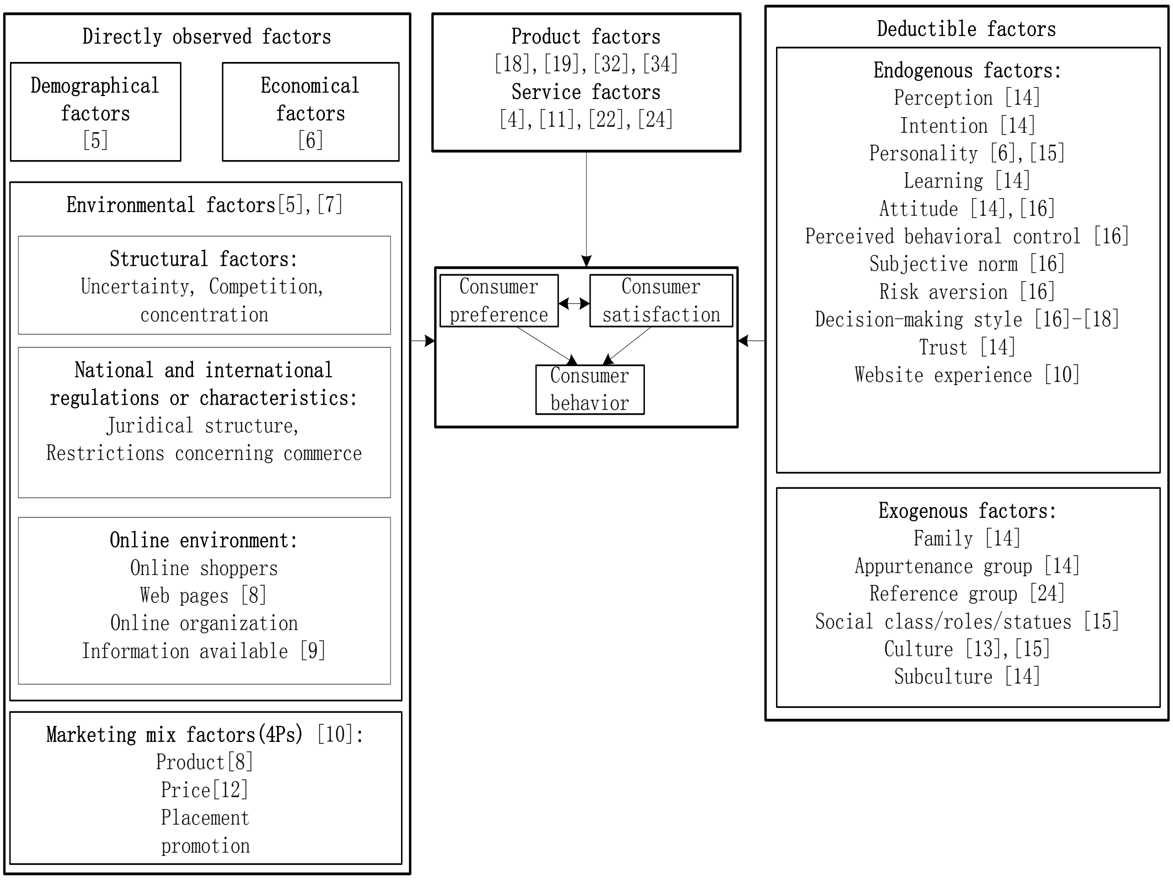

Figure 1. Influential factors of consumer preference in previous researches

In this paper, we utilize a classical analytical measure——MLR (multiple linear regression), because it is most useful when it comes to understanding the influence of several variables to a single outcome variable. However, considering the problem of data imbalance, the whole data are selected to be 50 groups with random proportional sampling. A new perspective is found to apply a meta-analytic review to analyze the influence of platform characteristics, product characteristics, and WOM (word of mouth) metrics [26]. Since Meta-analysis is a replicable and defensible method of synthesizing findings across studies [37], we creatively introduce the originally literature review tool——Meta-analysis to consolidate results of different groups.

3. MCPL: A COMSUMER PREFERENCE MODAL OF LAPTOP

In recent years, the user-generated contents become a valuable data sources for marketing research. Consumers can perceive the advantages/disadvantages about each specific product feature and generate comments that include their sentiments and preferences about these features. These comments are useful sources of information for product designers and manufacturers. Hence, we attempt to excavate consumer preference of a specific product through the impact of each product attribute on the consumers' overall satisfaction. A feature-based consumer preference model can be built from the features extracted from online product reviews. Prospectively, this model can give references for designers and manufacturers in developing or improving their product. In this study, we take the Acer laptop for example to build a conceptual model named MCPL (Model of Consumer Preference for Laptop), which is presented as below.

As shown in Figure 2, the MCPL is a hierarchical structure. The first level is the product itself. The second level is the typical factors that have effects on consumer preference according to the previews researches.

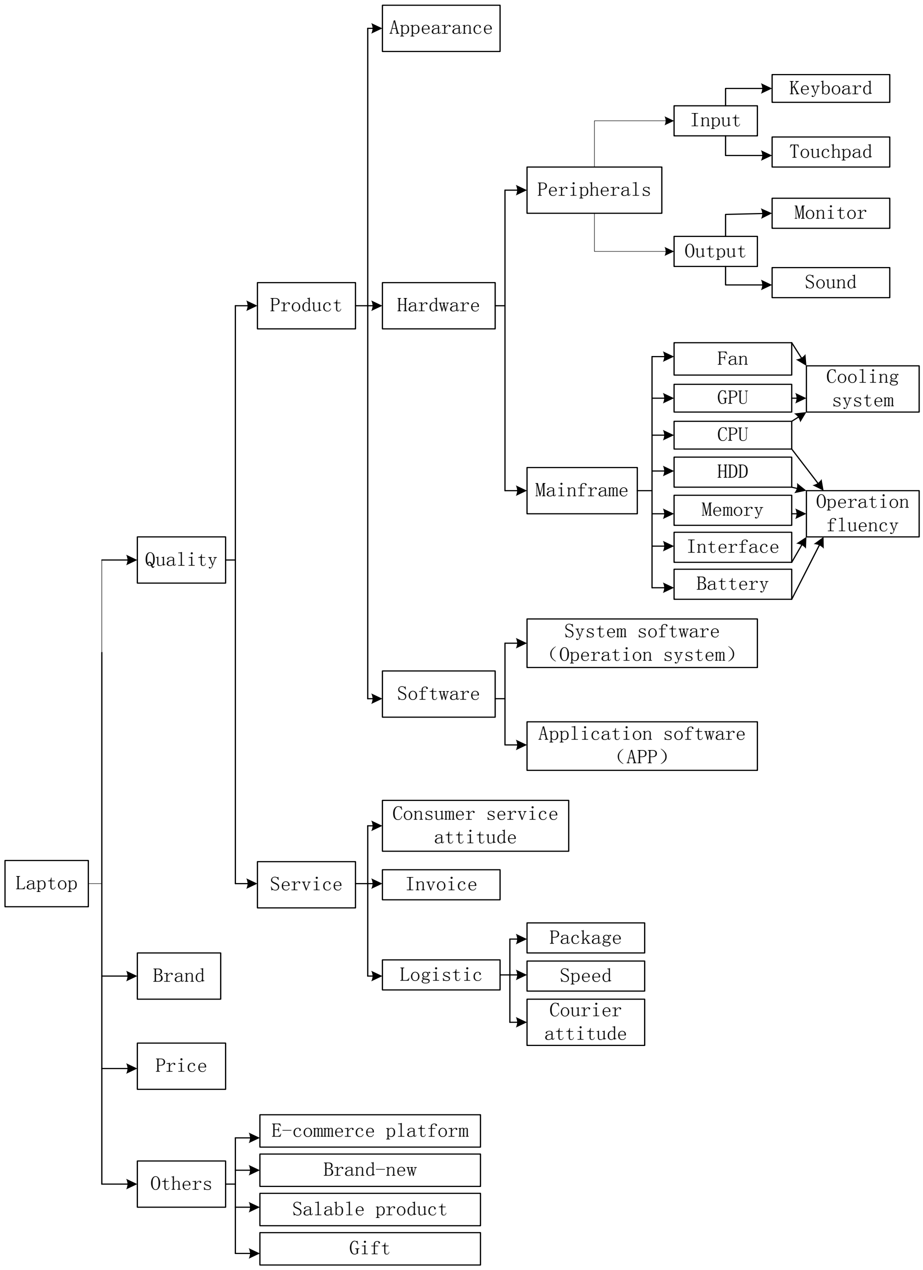

Figure 2. MCPL model of laptop

Among them, the quality is usually composed of product quality and service quality. For the former one, its' subordinate hierarchies are divided according to the laptops' structures and functions. For the latter one, its' three subordinate features are the main characteristics mentioned in online reviews. Besides, E-commerce platform, brand-new, salable product and gift are unconventional factors that is hard to conclude into the other three conceptions.

4. METHODOLOGY

The research procedure is shown in Figure 3. The online reviews of Acer laptop are collected from Amazon.cn, which includes overall score from 1 to 5, general comment and detailed comment. The software Bazhuayu is used to collect online reviews automatically. It can eliminate duplicated data easily.

The research procedure includes four main steps : (1)Data pre-processing and feature extraction; (2) conceptual model developing; (3) data analysis including feature frequency counting, correlation analysis, multiple linear regression and Meta-analysis; (4) result analysis. As a result, a list of candidate improvement is

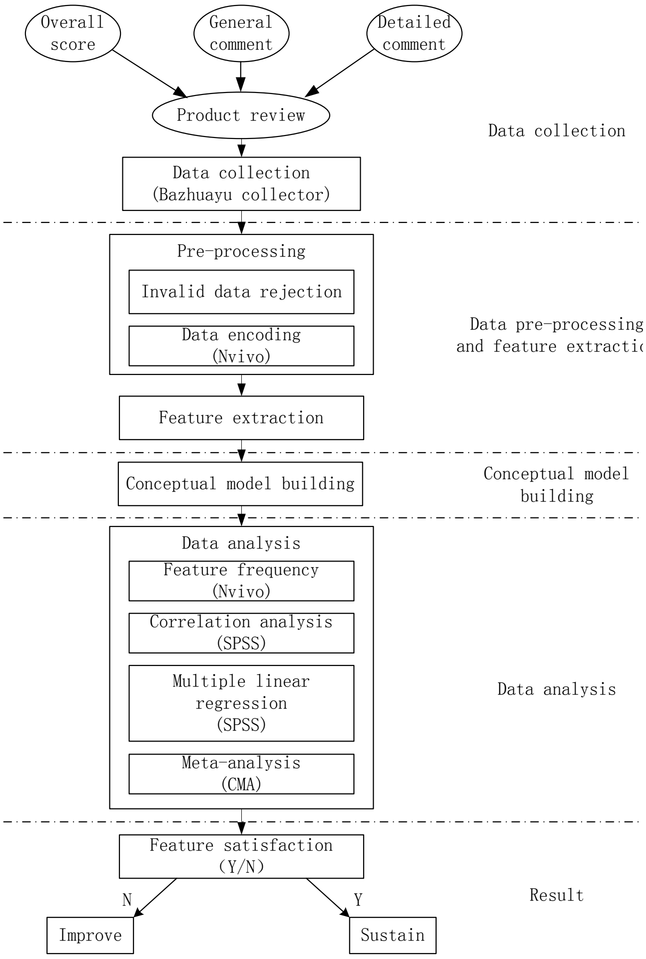

Figure 3. Overview diagram of research procedure

proposed for laptop manufacturers. By assessing the satisfaction degree of each feature, we can discern whether consumers are satisfied or unsatisfied with them.

Two theoretical bases are adopted to support this research. On the one hand, the classical performance model contributes an implication to our opinion. Because it reveals that the profits brought by the product features, or the extent to which consumers' needs are meet, directly determine the consumers' satisfaction level [38]. In other words, product feature performance is the antecedent of consumer satisfaction. On the other hand, according to RL Oliver [39], consumers' satisfaction determines their product preference to some extent. Therefore, combining with the former two opinions, we can safely come to a conclusion that the effect levels of product features on consumers' overall satisfaction can represent consumers' product feature preference.

5. DATA PROCESSING AND ANALYSIS

5.1 Data pre-processing and feature extraction

Totally 6531 reviews of Acer laptop are collected through Amazon.cn until May 20, 2016. Online reviews collected by Bazhuayu are text documents. So, it must be converted into quantitative data for further analysis. Furthermore, we need to remove invalid data. For instance, there are numerous consumer reviews only containing brief words like "good", "terrible", "I like it", or other meaningless words. Those expressions make it impossible to recognize product features influencing consumers' satisfaction. Thus, this kind of reviews should be eliminated. The valid data after pre-processing includes 4894 online reviews. With Nvivo 10, 26 product features of laptop that affect consumer's satisfaction are recognized. In addition, consumer satisfaction degree for each feature is encoded into 3 levels, in which "-1" represents dissatisfaction, "1" indicates satisfaction and "0" means indifferent or unmentioned.

5.2 Conceptual model

We summarize and classify the keywords of potential candidate attributes of laptop based on reading the online review text. After reading moderate amount of them, the high-mentioned features and its' representative descriptors can be summarized. Table 1 gives a showcase of the keywords summary. Subsequently, the keywords are inputted into Nvivo 10, which helps us to encode the whole text reviews. With Nvivo 10, reference nodes that represent product attributes can be established automatically and a frequency counting of each node can be calculated. As a result, 26 product features are captured, including logistics, invoice, appearance, consumer service attitude, E-commerce platform, brand-new, salable product, package, monitor, operation system, APP(Software), touchpad, operation fluency, price, fan, battery, sound, keyboard, cooling system, CPU (Central Processing Unit), interface, brand, memory, free gift, GPU (Graphics Processing Unit), and HDD (Hard Disk). A feature-based consumer preference conceptual model MCPL is shown in Figure 2.

Table 1. Keywords summary of separate nodes

No.	Node (feature)	Key words
1	Operation system	Win, Windows, Operation system, Compatible, Compatibility, Lin, Linux, OS
2	Cooling system	Heating, Cooling, Heat-removal, Hot, Burning, Temperature
3	Battery	Battery, Power, Endurance, Durable, Lasting, Standby time

5.3 Correlation analysis and multiple linear regressions

Before conducting multiple linear regressions, there should be a correlation analysis to make sure the degree of association between features and consumer satisfaction. In this research, we conduct Pearson correlation analysis of two-sides by using SPSS. To verify whether the overall satisfaction is definitely effected by these attributes, the multiple linear regressions are conducted. We assume that the variables are independent of each other. Considering the data imbalance of the 4894 product reviews, a random cluster sampling method is adopted to extract 50 groups by separately taking 20 data stochastically from five kinds of reviews with scores ranging from 1 to 5. Therefore, the multiple regression analyses are conducted 50 times correspondently for the 50 groups of datasets.

5.4 Meta-analysis

Meta-analysis is originally an approach applied in restating the existing empirical literatures. It is a replicable and defensible method of synthesizing findings across studies. Therefore, in order to increase the statistical testing effectiveness, we creatively introduce it to consolidate results of different groups with CMA (Comprehensive Meta-analysis) in this research. The initial data required in meta-analysis of this research are the correlations and sample sizes in the front research.

There should be a homogeneity analysis before meta-analysis. It tests whether the assumption that all of the effect sizes are estimating the same population mean is a reasonable assumption. If it is rejected, the distribution of effect sizes is assumed to be heterogeneous [24]. The significant Cochran's Q-test of homogeneity and the high scale-free index of homogeneity I^2 are used to confirm heterogeneity. The evaluating indicator ("Q" and "I^2") can be calculated by the following formula:

$$Q = \sum(\omega \times {Z_r}^2) - \frac{[\sum(\omega \times Z_r)]^2}{\sum \omega} \tag{1}$$

$$I^2 = \begin{cases} \frac{Q-(df_1-1)}{Q} \times 100\%, Q > df_1 \\ 0 \qquad\qquad\qquad , Q \le df_1 \end{cases} \tag{2}$$

(Z_r- the Fisher's Z_r; ω-the inverse variance weight; ES-effect size; df_1 equals the number of ESs – 1)

The Meta-analysis can be conducted by following steps. First, data standardization is performed by using the Fisher's Z_r transformation to transform the correlation coefficient into Z_r. Second, the inverse variance weight is calculated. Third, the mean effect size and its Z-test are conducted. At last, final outcomes can be converted back into "ES_r" with the inverse Z_r transformation. The involved formulas are demonstrated below:

(1) Fisher Z transformation of effect size:

$$Z_r = 0.5 \ln \frac{1+r}{1-r} \tag{3}$$

(Z_r- the Fisher's Z_r ; r- the correlation coefficient)

(2) standard error for the Fisher Z transformed effect size(se_{Z_r}):

$$se_{Z_r} = \frac{1}{\sqrt{n-3}}, \text{ n is the number of sets} \tag{4}$$

(3) the inverse variance weight(ω):

$$\omega = \frac{1}{{se_{Z_r}}^2} = \mathrm{n} - 3 \tag{5}$$

(4) the mean effect size of the Fisher Z transformed effect size($\overline{ES_{Z_r}}$):

$$\overline{ES_{Z_r}} = \frac{\sum \omega \times Z_r}{\sum \omega} \tag{6}$$

(5) standard error for the mean effect size of the Fisher Z transformed effect size($se_{\overline{ES_{Z_r}}}$):

$$se_{\overline{ES_{Z_r}}} = \frac{1}{\sqrt{\sum \omega}} \tag{7}$$

(6) Z-test for the mean effect size:

$$\mathrm{Z} = \frac{\overline{ES_{Z_r}}}{se_{\overline{ES_{Z_r}}}} \tag{8}$$

95% confident interval:

$$\text{Lower} = \overline{ES_{Z_r}} - 1.96(se_{\overline{ES_{Z_r}}}) \tag{9}$$
$$\text{Upper} = \overline{ES_{Z_r}} + 1.96(se_{\overline{ES_{Z_r}}})$$

(7) the back-transformed effect size (ES_r-interpreted as a correlation):

$$\mathrm{ES}_r = \frac{e^{2\overline{ES_{Z_r}}-1}}{e^{2\overline{ES_{Z_r}}+1}} \tag{10}$$

6.RESULT AND DISCUSSION

The frequencies of individual reference node, namely, product features are shown in Table 2, sorted by attribute frequency in descending order. For example, Operation fluency is mentioned 4643 times in online reviews, and invoice is mentioned 66 times. As seen from Table 2, we can understand the importance degree of

Table 2. Frequencies of product features mentioned in online reviews

No.	Feature	Frequency	Proportion	No.	Feature	Frequency	Proportion
1	Operation fluency	4643	25.43%	14	Memory	323	1.77%
2	Appearance	2359	12.92%	15	Brand	291	1.59%
3	Price	2091	11.45%	16	Sound	224	1.23%
4	Monitor	1690	9.26%	17	Battery	218	1.19%
5	Operation system	942	5.16%	18	Brand-new	198	1.08%
6	Logistic	769	4.21%	19	Gift	195	1.07%
7	Cooling system	758	4.15%	20	GPU	158	0.87%
8	Consumer service attitude	708	3.88%	21	CPU	152	0.83%
9	Salable product	441	2.42%	22	Fan	146	0.80%
10	Keyboard	422	2.31%	23	Touchpad	137	0.75%
11	HDD	391	2.14%	24	Package	111	0.61%
12	APP	386	2.11%	25	Interface	72	0.39%
13	E-commerce platform	366	2.00%	26	Invoice	66	0.36%

every feature. The features with higher frequencies may have more effect on consumer preference than the features with lower frequencies.

The Pearson correlation analysis of two-sides reveals the correlation coefficient and its' significance between individual factor's satisfaction and the overall satisfaction. According to the result of Pearson correlation analysis, the 26 attributes are all significantly correlated with consumers' overall satisfaction in different significant levels of 0.01 or 0.05 except for the interface.

Multiple linear regressions are conducted after correlation analysis to explore whether the overall satisfaction is exactly influenced by these attributes and evaluate their respective impact degree. All of the 50 groups of data possess great significant in 0.001 level. The overall goodness of fit is good, since the R^2 of the 50 groups range from 0.583 to 0.705. By accumulating the frequencies of significant variables of individual group that influence the overall satisfaction, a preliminary conclusion about ranking of the attributes' importance can be drown. Summary of feature significance frequency in 50 regression analyses are shown in Table 3.

Table 3. Summary of feature significance frequency in 50 regression analyses

No.	Feature	Frequency	Proportion	No.	Feature	Frequency	Proportion
1	Operation fluency	50	100%	14	Invoice	8	16%
2	Price	36	72%	15	Brand-new	8	16%
3	Consumer service attitude	31	62%	16	Salable product	8	16%
4	Appearance	27	54%	17	Monitor	8	16%
5	Operation system	22	44%	18	APP	8	16%
6	Logistic	18	36%	19	Fan	6	12%
7	GPU	16	32%	20	Package	5	10%
8	e-commerce platform	15	30%	21	Memory	4	8%
9	Keyboard	13	26%	22	HDD	4	8%
10	Gift	13	26%	23	CPU	3	6%
11	Cooling system	12	24%	24	Interface	3	6%
12	Sound	11	22%	25	Battery	1	2%
13	Brand	10	20%	26	Touchpad	0	0%

To make the research more rigorous and authentic, meta-analysis is applied to integrate the results of 50 groups. The result of heterogeneity analysis is displayed in Table 4.

Table 4. Result of heterogeneity analysis

Feature	Q	I^2	Feature	Q	I^2
Operation fluency	46	0	Brand	36	0
Consumer service attitude	46	0	Sound	42	0
Price	68	28	Gift	40	0
E-commerce platform	56	13	Battery	28	0
Logistic	33	0	Fan	43	0
Appearance	102	52	Interface	28	0
Monitor	76	35	Invoice	34	0
Brand-new	25	0	Package	42	12
Keyboard	30	0	CPU	24	0
Salable product	21	0	Memory	33	0
GPU	30	0	Touchpad	38	0
Cooling system	45	0	HDD	35	0
Operation system	46	0	APP	100	51

As mentioned before, the Q and I^2 are used to confirm heterogeneity. For the attributes appearance and APP, their I^2 are beyond 50. Therefore, a sensitivity analysis should be conducted. After two groups of abnormal value are removed from appearance and one group is removed from APP, their I^2 separately decrease to 33 and 43. Then, the meta-analysis can be conducted. Result is displayed in Table 5. Setting df $_1$= number of ESs – 1(“ES” means Effect Size), if our calculated Q is less than df_1, we fail to reject the null hypothesis of homogeneity. That is to say, the fixed effect model is reliable enough. Otherwise, the random effect model will be better. As shown in Table 5, price, e-commerce platform, appearance, monitor, package, APP would better to adopt the random model because their Q is beyond the threshold, while the others should take the fixed one.

Using the estimated correlation coefficients, effect size(“ES”), dominant features’ performances of the laptop are demonstrated. Table 5 is sorted by descending order of the effect size. As we mentioned before, consumer satisfaction is affected by product feature performance. In addition, consumers’ satisfaction determines their product preference to some extent. Therefore, the effect levels of the product features on the overall consumer satisfaction can reveal the product feature preference ranking of consumers. It can be seen from the Table 5 that all the factors have significantly influence on consumer satisfaction except for HDD. According to Cohen’s “Rules-of-Thumb”, for the correlation coefficient ES, “0.10” represents a small effect, “0.25” indicates a medium effect, and “0.40” means a large one [40]. As a result, we can conclude that the operation fluency plays the most important role, while consumer service attitude and price hold moderate level. In addition, e-commerce platform, appearance, logistic, monitor, brand-new, keyboard, salable product, GPU, cooling system, operation system, brand, sound and gift also affect consumer preference. The remainder rarely has influence upon consumer satisfaction.

Further researches are supposed to excavate consumers’ attitudes toward each specific feature. Enterprises should explore whether the consumers are satisfied with each feature and what kind of merits/demerits really make a difference for consumers’ satisfaction. In consequence, measures can be taken to improve or sustain the product features referring to their preference ranking. According to our proposed MCPL model, implications can be drawn for the enterprise competition strategies to facilitate product design or improvement. To be specific, it can be implemented referring to feature preference in four dimensions. The first one is quality, and this dimension consists of two parts. One is the product quality. It can be seen that the operation fluency is the most important factor that affect consumer satisfaction. In this regard, consumers focus more on the operation system. Thus, countermeasures should be taken to improve the quality of operation system. In addition, appearance is another important factor that manufacturers should take into account when design a laptop. A portable and beautiful one will be more attractive. Attention should also be paid to enhance intuitive experiences such as visual perception (monitor and GPU), hand feeling(keyboard) and hearing sense(sound). Another quality is the service quality. A good consumer service attitude and a rapid delivery can contribute a lot to consumer satisfaction. The second dimension is price. A moderate price will appeal more consumers to purchase for the product. The third dimension is brand. A brand with good word of mouth will be more preferable. Within the fourth dimension, E-commerce platform, brand-new, salable product, gift can be more or less influential in consumer satisfaction.

What seems unforeseen is that the interface and the memory have significantly negative influence on consumer satisfaction. However, it is not indecipherable. The node proportions of them are respectively 1.77% and 0.39%. There are only few consumer reviews referring to interface and memory, and almost all of them are negative ones. Since we randomly sample 100 reviews in each group, most of them may not contain reviews refer to the two factors. As a result, the two factors’ satisfaction scoring “0” may account for a large proportion, which simulates the consequence to be significant superficially. what’s more, since the few reviews that do contain the two factors may be negative ones, coincidentally matching with a positive overall satisfaction, the outcome "seems" to be negative effects. Actually, from the very beginning, we assumed the variables to be independent, in other words, the variables do not have interaction effect on each other. Nevertheless, in reality, there do exist interactions, because consumer mostly can endure some non-fatal product defects as a quid pro quo for the low enough price, especially when these defects can be remedied such as installing memory module and conversion interface. Price advantage is one of the characteristics of the chosen laptop brand, which explains why consumers are generally satisfied with the product despite the slight unsatisfied with one or two particular features of it.

Table 5. Preference ranking of candidate features

Feature	Model	Effect size and 95% confidence interval			Test of null (2-Tail)		Heterogeneity		Standard Error	Sets	Sample size
		Point estimate	Lower limit	Upper limit	Z-value	P-value	Q	I^2			
Operation fluency	random	0.429	0.406	0.452	31.971	0.000	46	0	0.002	50	5000
	fixed	0.429	0.406	0.452	31.971	0.000				50	5000
Consumer service attitude	random	0.308	0.283	0.334	22.202	0.000	46	0	0.002	50	5000
	fixed	0.308	0.283	0.334	22.202	0.000				50	5000
Price	random	0.296	0.265	0.326	18.006	0.000	68	28	0.003	50	5000
	fixed	0.296	0.270	0.321	21.241	0.000				50	5000
E-commerce platform	random	0.227	0.199	0.256	15.017	0.000	56	13	0.002	50	5000
	fixed	0.227	0.201	0.254	16.117	0.000				50	5000
Appearance	random	0.209	0.175	0.243	11.857	0.000	70	33	0.003	48	4800
	fixed	0.209	0.182	0.237	14.497	0.000				48	4800
Logistic	random	0.195	0.168	0.222	13.790	0.000	33	0	0.002	50	5000
	fixed	0.195	0.168	0.222	13.790	0.000				50	5000
Monitor	random	0.147	0.113	0.181	8.326	0.000	76	35	0.003	50	5000
	fixed	0.147	0.120	0.175	10.337	0.000				50	5000
Brand-new	random	0.141	0.113	0.169	9.889	0.000	25	0	0.002	50	5000
	fixed	0.141	0.113	0.169	9.889	0.000				50	5000
Keyboard	random	0.138	0.111	0.166	9.695	0.000	30	0	0.002	50	5000
	fixed	0.138	0.111	0.166	9.695	0.000				50	5000
Salable product	random	0.129	0.097	0.161	7.881	0.000	21	0	0.002	38	3800
	fixed	0.129	0.097	0.161	7.881	0.000				38	3800
GPU	random	0.127	0.099	0.154	8.876	0.000	30	0	0.002	50	5000
	fixed	0.127	0.099	0.154	8.876	0.000				50	5000
Cooling system	random	0.122	0.094	0.150	8.552	0.000	45	0	0.002	50	5000
	fixed	0.122	0.094	0.150	8.552	0.000				50	5000
Operation system	random	0.105	0.077	0.133	7.327	0.000	46	0	0.002	50	5000
	fixed	0.105	0.077	0.133	7.327	0.000				50	5000
Brand	random	0.104	0.076	0.132	7.296	0.000	36	0	0.002	50	5000
	fixed	0.104	0.076	0.132	7.296	0.000				50	5000
Sound	random	0.102	0.074	0.131	7.005	0.000	42	0	0.002	48	4800
	fixed	0.102	0.074	0.131	7.005	0.000				48	4800
Gift	random	0.101	0.073	0.129	7.066	0.000	40	0	0.002	50	5000
	fixed	0.101	0.073	0.129	7.066	0.000				50	5000
Battery	random	0.088	0.060	0.115	6.112	0.000	28	0	0.002	50	5000
	fixed	0.088	0.060	0.115	6.112	0.000				50	5000
Fan	random	0.086	0.058	0.114	6.029	0.000	43	0	0.002	50	5000
	fixed	0.086	0.058	0.114	6.029	0.000				50	5000
Interface	random	-0.086	-0.116	-0.056	-5.596	0.000	28	0	0.002	43	4300
	fixed	-0.086	-0.116	-0.056	-5.596	0.000				43	4300
Invoice	random	0.083	0.055	0.111	5.770	0.000	34	0	0.002	50	5000
	fixed	0.083	0.055	0.111	5.770	0.000				50	5000
Package	random	0.064	0.030	0.098	3.661	0.000	42	12	0.003	38	3800
	fixed	0.064	0.032	0.096	3.893	0.000				38	3800
CPU	random	0.050	0.022	0.079	3.484	0.000	24	0	0.002	49	4900
	fixed	0.050	0.022	0.079	3.484	0.000				49	4900
Memory	random	-0.045	-0.073	-0.017	-3.155	0.002	33	0	0.002	50	5000
	fixed	-0.045	-0.073	-0.017	-3.155	0.002				50	5000
APP	random	0.034	-0.003	0.072	1.794	0.073	84	43	0.004	49	4900
	fixed	0.034	0.006	0.063	2.369	0.018				49	4900
Touchpad	random	0.029	0.001	0.057	2.033	0.042	38	0	0.002	50	5000
	fixed	0.029	0.001	0.057	2.033	0.042				50	5000
HDD	random	0.026	-0.002	0.054	1.829	0.067	35	0	0.002	50	5000
	fixed	0.026	-0.002	0.054	1.829	0.067				50	5000

7.CONCLUSION

This paper proposes a conceptual model of laptop and focuses on analyzing online consumers' feature preferences through online product reviews. Accordingly, we first extract features from enormous review contents. Subsequently, the conceptual model is developed for representing the consumer preference of laptop. Then, we conduct a correlation analysis to make sure whether these features do have relations with consumers' overall satisfaction. Furthermore, to identify the impact extent of these features to overall satisfaction, the multiple linear regressions are carried out for 50 times, followed by the creatively use of meta-analysis to consolidate the regression results. Drawing on the quantitative results, we figure out which product features of laptop primarily influence consumer preference. In consequence, the advantages of the product can be sustained and the weakness can be improved in ideal orders.

The results are of methodological and substantive interest. On the methodological issues, we provide a novelty approach to integrate results of different data groups by using meta-analysis while others mostly use it in reanalysis of different studies. For the substantive issues, the Utility Theory proposes that consumers make choices based on the expected outcomes of their decisions [41]. According to the New York Times in 2012, "reviews by ordinary people have become an essential mechanism for selling almost anything online" [42]. Thus, it is essential to improve customer satisfaction and identify the associated design attributes that would represent consumer preference to ensure sustained customer loyalty and strengthen competitiveness for the firm. Thereby, practical implications are able to be drawn for enterprise competition strategies to facilitate product design, improvement, or position as well as develop effective marketing strategies on the basis of features' importance ranking. For example, in the perspective of designers and manufacturers, the domain features such as operation fluency, consumer service attitude and price need to be fulfilled in advance. Efforts and costs should not be taken to develop inessential characters such as HDD and touchpad.

There are several limitations while conducting this research. First, some incentive and compensating measures of merchant may lead to bias expression of consumer satisfaction to the product. That may result into inauthentic in research. Second, consumer preference differs significantly across product categories and even one category of different brands [18], so the conclusion of this paper may not fit for other kinds of products. Besides, other brands of laptop are supposed to be involved. Additionally, because of culture differences, consumer preference may vary in different countries. Our further studies are aiming at comparing consumer preferences between different countries. Finally, the interaction effects between variables are not considered in this research, further work could focus on how to make up it.

ACKNOWLEDGEMENT

This research was supported by the National Social Science Foundation Project of China under Grant 16FGL014, and the Hebei Province Natural Science Foundation Project under Grant G2014202148.

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